# Reproducing Kernel Hilbert Spaces (2)

Manel Martínez-Ramón

ECE, UNM

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## The curse of dimensionality



In the previous lesson we used a nonlinear transformation to pass from of  $\mathbb{R}^2$  to  $\mathbb{R}^p$ ,  $p = \begin{pmatrix} 2+3 \\ 3 \end{pmatrix} = 10$ :

$$1, x_1, x_2, x_1^2, x_2^2, x_1x_2, x_1^2x_2, x_1x_2^2, x_1^3, x_2^3$$

In an input space of 2 dimensions, and with a Volterra expansion of order 5, we need 56 elements:

$$p = \left(\begin{array}{c} 2+5\\ 5 \end{array}\right) = 56$$

This is an example of the the curse of dimensionality, which we have to solve.

#### The Kernel trick



Trick to conjure up the curse of dimensionality:

- Find a method where we can work with expressions of *only the input space*. We have two fortunate facts:
- If an algorithm fits the Representer Theorem, a dual expression can be constructed as function of dot products between data.
- Punctions that are dot products in higher dimension Hilbert Spaces exist.

The Kernel trick is nothing but the use of these two facts together.

## The Representer Theorem



Representer Theorem (Kimeldorf and Wahba, 1971)

- $\varphi(\mathbf{x}_n) = \varphi_n \in \mathcal{H}$  where  $\mathcal{H}$  is a Hilbert space with dot product  $\langle \varphi_i, \varphi_j \rangle) K(\mathbf{x}_i, \mathbf{x}_j)$
- $\Omega:[0,\infty)\to\mathbb{R}$  strictly monotonic increasing function
- $V: (\mathcal{X} \times \mathbb{R}^2)^N \to \mathbb{R} \cup \{\infty\}$  Arbitrary loss function

Then:

$$f^* = \min_{f \in \mathcal{H}} \left\{ V\left( (f(\varphi_1), \varphi_1, y_1), \dots, (f(\varphi_N), \varphi_N, y_N) \right) + \Omega(\|f\|_2^2) \right\}$$

admits a representation

$$f^*(\cdot) = \sum_{i=1}^N \alpha_i K(\cdot, \mathbf{x}_i), \quad \alpha_i \in \mathbb{R}, \quad \boldsymbol{\alpha} \in \mathbb{R}^N$$

#### Volterra revisited: dual



- Let us consider the Volterra case again.
- The estimator is

$$y[n] = \mathbf{w}^{\top} \boldsymbol{\varphi}(\mathbf{x}_n)$$

• and the MMSE solution as

$$\mathbf{w} = (\boldsymbol{\Phi} \boldsymbol{\Phi}^{\top})^{-1} \boldsymbol{\Phi} \mathbf{y}$$

where  $\Phi$  is a matrix that contains all column vectors  $\varphi(\mathbf{x}_n)$ .

### Volterra revisited: dual



ullet Now, we take the fact that vector  ${f w}$  is a linear function of the data as

$$\mathbf{w} = \sum_{n=1}^{N} \alpha_n \boldsymbol{\varphi}(\mathbf{x}_n) = \boldsymbol{\Phi} \boldsymbol{\alpha}$$

• We use this and previous equations together to obtain

$$\boldsymbol{\Phi} \boldsymbol{\alpha} = (\boldsymbol{\Phi} \boldsymbol{\Phi}^{\top})^{-1} \boldsymbol{\Phi} \mathbf{y}$$

• By matrix manipulation we get the expression

$$\boldsymbol{lpha} = (\boldsymbol{\varPhi}^{\top} \boldsymbol{\varPhi})^{-1} \mathbf{y}$$

 $\bullet$  Here, matrix  $\mathbf{K} = \boldsymbol{\varPhi}^{\top}\boldsymbol{\varPhi}$  contains all dot products between data.

### Volterra revisited: kernel



• Also, since  $\mathbf{w} = \mathbf{\Phi} \boldsymbol{\alpha}$  the estimator

$$y[m] = \mathbf{w}^{\top} \boldsymbol{\varphi}(\mathbf{x}_m)$$

becomes

$$y[m] = \boldsymbol{\alpha}^{\top} \boldsymbol{\varPhi}^{\top} \boldsymbol{\varphi}(\mathbf{x}_m)$$

• This, in scalar notation is

$$y[m] = \sum_{n=1}^{N} \alpha_n < \varphi(\mathbf{x}_n), \varphi(\mathbf{x}_m) >$$

where  $\langle \cdot, \cdot \rangle$  denotes dot product between vectors.

### Volterra revisited: kernel



- The next step would consist of finding a dot product in the higher dimension space that can be expressed as a function of the input space only.
- For the order 3 Volterra, this dot product is

$$<\varphi(\mathbf{x}_n), \varphi(\mathbf{x}_m)>=(\mathbf{x}_n^{\top}\mathbf{x}_m+1)^3$$

 Hence, we have a compact representation that avoids the curse of dimensionality, since the term inside the parenthesis is just a scalar.

### Volterra revisited:kernel

 $\sqrt{3}x'_2$ , 1]<sup> $\top$ </sup>

 $(\mathbf{x}^{\top}\mathbf{x}'+1)^3 = (x_1x_1' + x_2x_2' + 1)^3$ 



Let's prove it. Let  $\mathbf{x}_1 = [x_1, x_2]^{\top}$  and  $\mathbf{x}' = [x'_1, x'_2]^{\top}$  be two vectors:

$$= x_1^3 x_1'^3 + x_2^3 x_2'^3 + 3x_1^2 x_2 x_1'^2 x_2' + 3x_1 x_2^2 x_1' x_2'^2 + 3x_1^2 x_1'^2 + 3x_2^2 x_2'^2 + 6x_1 x_1' x_2 x_2' + 3x_1 x_1' + 3x_2 x_2' + 1 =$$

$$(x_1 x_1' + x_2 x_2' + 1)^3 =$$

$$= [x_1^3, x_2^3, \sqrt{3} x_1^2 x_2, \sqrt{3} x_1 x_2^2, \sqrt{3} x_1^2, \sqrt{(3)} x_1^2, \sqrt{6} x_1 x_2, \sqrt{3} x_1, \sqrt{3} x_2, 1].$$

Thus  $(\mathbf{x}^{\top}\mathbf{x}' + 1)^3$  is the dot product of the Volterra expansion of the two vectors, up to some constants.

 $[x_1'^3, x_2'^3, \sqrt{3}x_1'^2x_2', \sqrt{3}x_1'x_2'^2, \sqrt{3}x_1'^2, \sqrt{3$ 

#### Outcomes of this lesson



- We have seen an example of a simple problem that cannot be solved using a linear classifier.
- A nonlinear estimator can be constructed by a nonlinear transformation to a space of higher dimension.
- This solution suffers from the curse of dimensionality.
- Nevertheless, using the Representer Theorem and finding a kernel dot product in this space, the problem is solved.